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Research Paper

AI POWERED LIVER DISEASE DETECTION USING SOCIAL SPIDER OPTIMIZATION

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ABSTRACT

In recent years, the rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly transformed image classification tasks across diverse domains such as healthcare, agriculture, and security. Traditionally, image classification was performed manually, requiring domain experts to visually analyze features such as shape, color, and texture—an approach that is time-consuming, error-prone, and heavily reliant on human judgment. These manual systems often lack scalability and consistency, especially when processing large volumes of images, leading to inefficiencies in real-world applications like medical diagnostics, object detection, or species identification. Statistical studies reveal that manual classification systems yield lower accuracy, with human error rates ranging from 10–25%, compared to CNN-based systems that achieve over 95% accuracy on benchmark datasets. The motivation for this project stems from the pressing need to replace inefficient manual methods with an automated, accurate, and scalable solution. Our objective is to design and implement a CNN-based image classification system that accepts user-uploaded images, performs preprocessing, extracts hierarchical features using a deep CNN architecture, classifies the image through a softmax layer, and delivers a prediction result in real-time. The proposed system leverages Python, TensorFlow/Keras, and possibly a graphical interface via Tkinter, offering an end-to-end automated pipeline. It eliminates the need for human involvement in image labeling, reduces errors, speeds up the process, and can be deployed in both academic and industrial scenarios. Furthermore, the system is flexible and extensible, allowing it to be adapted to various datasets and classification tasks. By automating image classification with CNN, this project not only improves accuracy and efficiency but also democratizes access to intelligent visual recognition tools, supporting smarter and more reliable decision-making in fields where precision is critical. The ultimate goal is to create a robust, real-time, and user-friendly solution that addresses the shortcomings of manual systems and embraces the potential of AI-driven technology.

Keywords: Liver Disease Detection, Convolutional Neural Networks (CNN), Image Classification, Deep Learning, Social Spider Optimization.

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INTRODUCTION

Liver diseases represent a significant global health challenge, particularly in India, where the burden of liver-related ailments is rising due to factors like unhealthy lifestyles, alcohol consumption, viral infections, and genetic predispositions.According to the World Health Organization (WHO), liver disease is one of the leading causes of mortality worldwide, and India is no exception. The prevalence of liver diseases, such as Hepatitis B, Hepatitis C, and cirrhosis, has escalated significantly in the last few decades.In India, studies show that nearly 10-20% of the population is affected by some form of liver disease, contributing to over 500,000 deaths annually. This alarming statistic underscores the importance of early diagnosis, which can significantly improve treatment outcomes. Conventional methods of diagnosing liver diseases are often slow, require invasive procedures, and depend heavily on human expertise, which can result in misdiagnosis

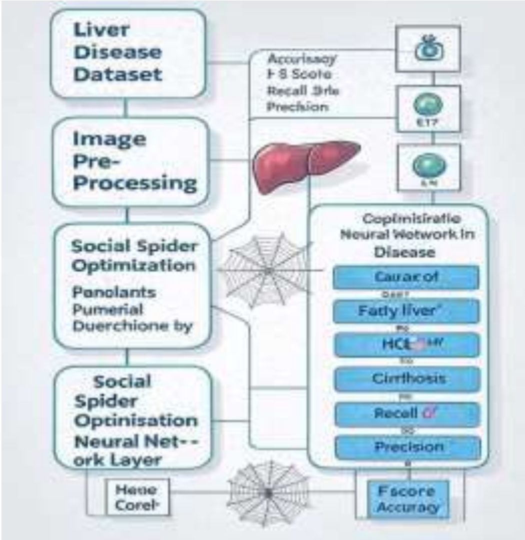

Fig. 1: Workflow diagram of ai-powered liver disease detection using social spider optimization.

Recent advancements in artificial intelligence (AI) and machine learning (ML) offer promising solutions to these challenges by enabling faster, more accurate, and non-invasive diagnostic tools.

2. LITERATURE SURVEY

Performing feature extraction is one of the traditional techniques for liver and tumour segmentation, followed by classification. To segment the liver Bastian et al. [1] used intensity feature later applied a super-pixel Simple Linear Iterative Clustering (SLIC) approach and an AdaBoost algorithm to achieve a Dice rate of 92.13% on 16 abdomen CT test images. Ali et al. [2] to extract the CT liver boundary used first order statistical features of the liver image, later for lesions classification a k-Mean classifier based on the distance and color is used. Chang et al. [3] segmented the tumors using a binary logistic regression analysis (a region growing algorithm), based on the extraction of texture, shape, and kinetic curve features, to classify the segmented tumors into benign or malignant. To define the complexity of tumor segmentation problems the extracted features may not be sufficient this is a drawback of traditional approaches. Hence, more sophisticated features must be investigated. Deep learning approaches makes full use of the database, i.e., to train a set of convolutional features that can describe the segmentation problem, the CT images and the corresponding Ground Truth (GT) segmentations by the radiologists. Generally, to learn the problem deep approaches use a huge number of parameters (i.e., millions). In the last decade, Convolutional Neural Networks (CNN) architectures have achieved outstanding performance in liver and lesions segmentations. (a) Separate liver or lesion segmentation approaches Liver segmentation is a primary step in many CAD systems for liver cancer or other liver diseases. Hu et al. [4] worked on a 3D CNN model, to provide an initial prior segmentation to segment the liver. Based on image appearance to provide the final segmentation, the surface of the prior segmentation was adaptability evolved. Further, throughout the literature different deep learning procedures for lesion segmentation were implemented. Bi et al. [5] used a deep residual network (Resnet) [6] for liver lesions segmentation. Han et al. [7] segmented the liver lesions automatically by building a CNN model. Here we are focusing on joint liver and lesion segmentation, a more intensive outline of the related joint methods is provided below. (b) Joint approaches for liver and lesion segmentations, these approaches can be categorized as one stage or cascade. Here we will briefly outline each category. One stage deep learning approach attempts to segment the liver and its lesions using one deep CNN stage. Korabelnikov et al. [8] obtained binary segmented image using a segmentation framework which consists of a pre-processing step, a pixel-wise classification using pre-trained CNN (AlexNet) and smoothing and thresholding as post-processing step. Badrinarayanan et al. [9] used Cascaded deep learning approaches attempt to segment the liver and lesion in more than one stage by using VGG Signet model. Bellver et al. [10] used two cascaded VGG16 models, the first one produces the liver segmentation, & it will be the input for the second VGG16 model, which produces the lesion segmentations. Vorontsov et al.used a two cascaded fully convolutional networks model for the joint segmentation of the liver and lesions from CT images. The model was built that were trained end-to-end to segment the liver and lesions, respectively. In detail, different traditional and deep learning methods are used either for liver segmentation or tumor segmentation or both.

3. PROPOSED METHODOLOGY

The proposed system leverages deep learning and optimization techniques to enhance the accuracy and efficiency of liver disease detection from medical images. Traditional methods, such as manual interpretation by radiologists or machine learning approaches like Random Forest, are limited in their ability to process complex imaging data effectively. To overcome these limitations, the proposed system integrates deep neural networks (DNNs) with Social Spider Optimization (SSO) for superior performance in liver disease classification. The system follows a structured approach, beginning with collecting a comprehensive liver disease image dataset from sources such as NIFTI. Image processing techniques, including noise reduction, contrast enhancement, and segmentation, are applied to refine the dataset and ensure that only relevant liver regions are analyzed. Unlike traditional machine learning models that require extensive feature engineering, the proposed system utilizes pre-trained deep learning models—CNN —which automatically extract high-level features from medical images.

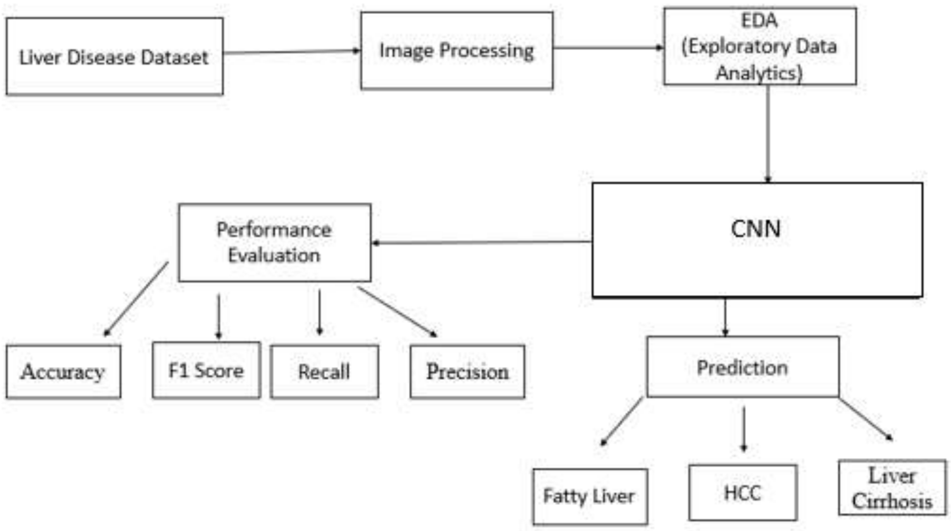

Fig.2: Liver disease prediction using cnn workflow.

Dataset: Fatty Liver, Hepatocellular Carcinoma, and Liver Cirrhosis. Each image is collected under controlled imaging protocols to ensure consistency in resolution, contrast, and orientation. We perform an initial audit of the dataset to confirm correct labeling and remove duplicates or severely corrupted files. Metadata such as patient age, imaging device parameters, and acquisition date are recorded alongside each image to facilitate later subgroup analyses or bias assessments. By carefully documenting the provenance and characteristics of the dataset at the outset, we establish a transparent and reproducible foundation for all subsequent experiments.

Image Preprocessing Raw medical images often vary in size, lighting, and noise, which can confound downstream learning. To standardize inputs, each image is first resized to a uniform dimension of 64×64 pixels. This size strikes a balance between retaining salient structural features and limiting computational overhead. We then apply pixel-value normalization, scaling the RGB channels to the [0,1] range, which accelerates CNN convergence and mitigates bias from unusually bright or dark scans. To enhance robustness, we also incorporate optional data augmentation steps—random rotations, horizontal flips, and small shifts—during training. Finally, all images are converted into NumPy arrays and, where appropriate, one-hot encoded into categorical labels. These preprocessing routines ensure that our model ingests clean, homogeneous data and is less prone to overfit minor artifacts.

Proposed SSO-CNN Model Building At the heart of this research is a two-stage feature extraction and classification pipeline combining Social Spider Optimization (SSO) with a Convolutional Neural Network (CNN). First, we flatten each preprocessed image into a 1D vector and feed it into our custom SimpleSSO algorithm, which treats the number of PCA components as agents in a search space. Each agent represents a candidate dimensionality; through iterative fitness evaluations based on reconstruction mean-squared error, SSO dynamically identifies the optimal reduced feature space. Once the optimal component count is found, we apply PCA to project the data into this lower-dimensional subspace. Next, these distilled features are reshaped (or concatenated as additional channels) and used to train a lightweight CNN—two convolutional layers with ReLU activations, max-pooling, flattening, and a final dense softmax layer matching the number of classes. This hybrid SSO-CNN approach leverages the global search capability of SSO to fine-tune feature selection before feeding the most informative patterns into the CNN for robust classification.

Performance Evaluation: A rigorous assessment of model efficacy requires multiple complementary metrics. We partition our dataset into 80% training and 20% testing sets, with stratified sampling to preserve class balance. During training, we monitor accuracy, loss, and validation curves to detect over- or underfitting. Once training concludes, we evaluate the CNN on the held-out test set, reporting accuracy, precision, recall, and F1-score for each class. A confusion matrix further highlights systematic misclassifications, while ROC curves and area under the curve (AUC) metrics assess discriminative power across decision thresholds. To ensure stability, we repeat the entire training-evaluation cycle across multiple random seeds and report mean ± standard deviation for each key metric. This multifaceted evaluation framework not only quantifies overall performance but pinpoints strengths and weaknesses of the SSO-enhanced feature extraction.

Prediction on New, Unseen Test Data: Demonstrate real-world applicability by deploying the trained SSO-CNN model on a separate **unseen test dataset**, ideally sourced from different imaging centers or acquired at later dates. Each new image undergoes the identical preprocessing (resizing, normalization, PCA projection with the learned components) before being fed into the CNN for inference. We record the model's predicted labels and probabilities, overlaying them on the input images for qualitative inspection. A domain expert then reviews a subset of these predictions to validate clinical relevance and flag any glaring errors. By comparing the model's performance on truly novel data against its original test metrics, we gauge its **generalizability** and readiness for potential integration into decision-support pipelines in clinical settings. This final step completes our research cycle, providing both quantitative and qualitative evidence of the model's utility beyond the confines of the training dataset

Data Splitting & Preprocessing: The dataset is carefully divided into training and testing subsets to ensure robust model evaluation and prevent data leakage. Typically, an 80:20 split is employed, where 80% of the images are used for training the model and the remaining 20% are reserved for testing its performance on unseen data. Before feeding the images into the model, extensive preprocessing is performed: all images are resized to a consistent dimension (e.g., 64×64 pixels) to standardize input size, and pixel values are normalized to a scale between 0 and 1 to improve model convergence during training.

Data Preprocessing

The image preprocessing pipeline for liver disease detection begins with raw medical images, such as MRI, CT, or ultrasound scans, which vary in size, lighting, and noise levels, potentially confounding downstream analysis. To address this, each image is resized to a uniform 64×64 pixels dimension, striking a balance between preserving critical structural features and reducing computational overhead. Pixel-value normalization then scales the RGB channels to a range, enhancing CNN convergence and mitigating biases from uneven brightness or darkness. Noise reduction is achieved through Gaussian filtering, while contrast enhancement via histogram equalization improves the visibility of liver structures and disease features. Optional data augmentation, including random rotations, horizontal flips, and small shifts, is applied during training to bolster model robustness. Finally, segmentation isolates relevant liver regions, and the preprocessed images are converted into NumPy arrays, with categorical labels one-hot encoded where appropriate, ensuring the model receives clean, homogeneous data less prone to overfitting minor artifacts. This comprehensive preprocessing pipeline, as depicted in Fig. 3, is essential for preparing the dataset for the subsequent SSO-CNN model.

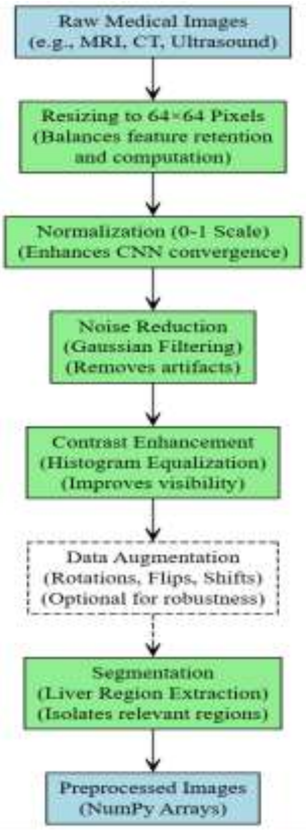

Fig. 3: Image Preprocessing Pipeline for Liver Disease Detection.

Proposed CNN (Convolutional Neural Network).

A Convolutional Neural Network (CNN) is a deep learning architecture highly effective for image classification tasks due to its ability to automatically extract and learn hierarchical features from raw pixel data without manual intervention. Inspired by the human visual system, CNNs utilize key components such as convolutional layers to detect spatial patterns (e.g., edges, textures), ReLU activation functions to introduce non-linearity, pooling layers to reduce spatial dimensions and computational load, and fully connected layers to interpret the extracted features for final classification. In the proposed system, input images are resized (e.g., 64×64×3 for RGB) and passed through a series of convolutional and pooling layers, followed by a flattening step that prepares the data for dense layer processing. Optimization techniques such as Principal Component Analysis (PCA) and Social Spider Optimization (SSO) are employed during preprocessing to enhance computational efficiency and model accuracy. Finally, the output layer with softmax activation generates probability scores for class prediction, completing the end-to-end learning pipeline.

4. RESULTS

The proposed liver disease detection system comprises multiple modules that work cohesively to deliver accurate classification results using deep learning. The User Authentication Module ensures secure access, allowing only registered users to use core functionalities such as prediction and model training. The Image Dataset Loading & Preprocessing module efficiently loads and normalizes medical images, resizing them to 64×64 pixels for consistency and storing preprocessed data for reuse. To optimize performance, a hybrid approach using Principal Component Analysis (PCA) and Social Spider Optimization (SSO) is employed. SSO, a nature-inspired metaheuristic, determines the optimal number of principal components by minimizing reconstruction error, enhancing dimensionality reduction without compromising essential data patterns. The CNN Model Creation & Training module constructs a convolutional neural network with convolutional, pooling, and dense layers, capped by a softmax output for multi-class classification. If a pre-trained model is available, it is loaded to save computational resources. The model's training performance is tracked and visualized using a simple accuracy history display.

The dataset used in this project includes labeled medical images categorized into three liver disease conditions: Fatty Liver, Hepatocellular Carcinoma (HCC), and Liver Cirrhosis. Each class is stored in a separate folder and comprises real-world diagnostic images exhibiting class-specific features. Fatty Liver images typically show bright echogenic regions indicating fat accumulation, with patterns common to both NAFLD and AFLD. Hepatocellular Carcinoma images include irregular masses and necrotic areas indicative of malignant growths, aiding in the early detection of liver cancer. Liver Cirrhosis images capture scarring, fibrosis, and architectural distortion, reflecting long-term liver damage. This rich, varied dataset allows the CNN model to learn and differentiate intricate features relevant to each disease class, leading to improved diagnostic accuracy and real-time application potential in clinical decision support systems.

Fig.4 Homepage

The homepage provides a navigation bar at the top with "HOME", "Login", and "Signup" options for user interaction. Below this, a brief welcome message, "Welcome Please Sign in/Up", encourages users to either log in or create a new account. The central part of the page emphasizes the core functionality: "Liver Disease Detection using Social Spider Optimization & Artificial Intelligence Pre-trained algorithms.

Fig 5 User Login Screen

The image shows a login page for a "Liver Disease prediction" system. “Username" and "Password" are clearly labeled input fields for user credentials. "Enter Username" and "Enter Password" are placeholder hints within the input fields. "login" is a submit button to initiate the login process.

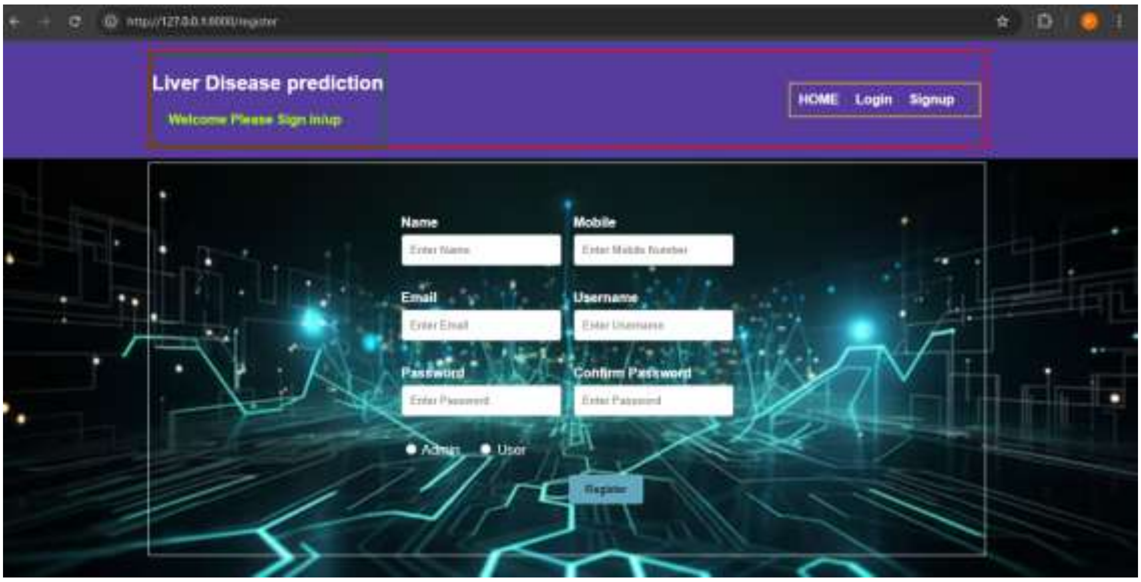

Fig 6 Signup Screen

The Figure shows a registration or signup form.Name: Field for entering a name, with the placeholder "Enter Name". Mobile: Field for entering a mobile number, with the placeholder "Enter Mobile Number". Email: Field for entering an email address, with the placeholder "Enter Email". Username: Field for entering a username, with the placeholder "Enter Username". Password: Field for entering a password, with the placeholder "Enter Password". Confirm Password: Field for confirming the password, with the placeholder "Enter Password". User Type Selection: Two radio buttons or checkboxes to select between "Admin" and "User". Register Button: A button labeled "Register" to submit the form.

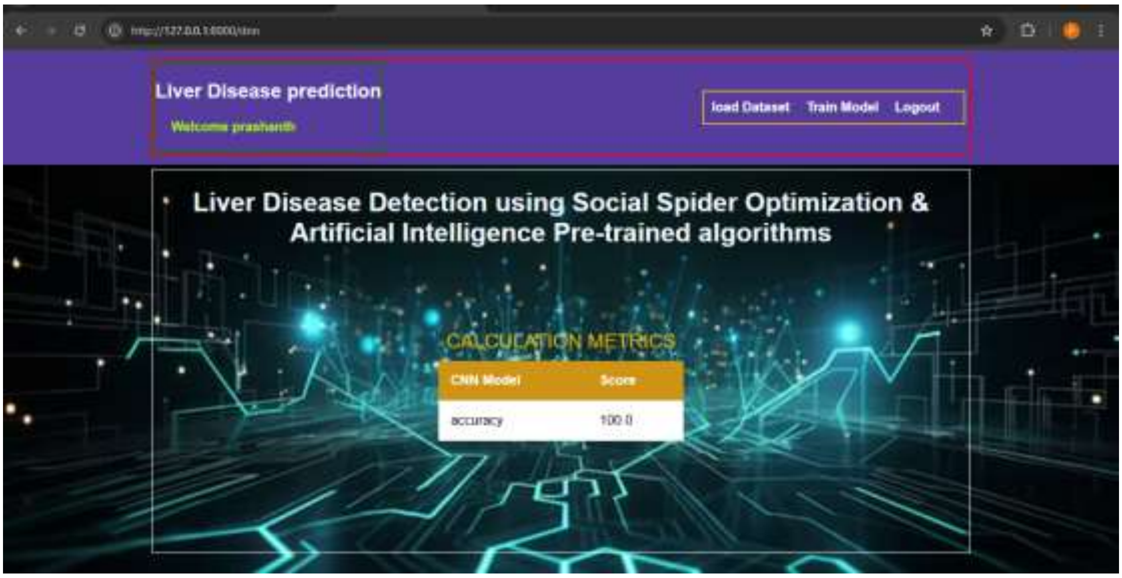

Fig 6 CNN Model Calculation Metrics

The Figure shows that the CNN model.

- **Calculation Metrics:** This is the title or heading, indicating that the information presented is related to performance metrics.
- **CNN Model:** This specifies that the metrics shown are for a Convolutional Neural Network (CNN) model.
- **Score:** This likely refers to a performance score or metric.
- **Accuracy:** The specific metric being displayed is accuracy.
- **100.0:** The CNN model achieved a perfect accuracy score of 100.0.

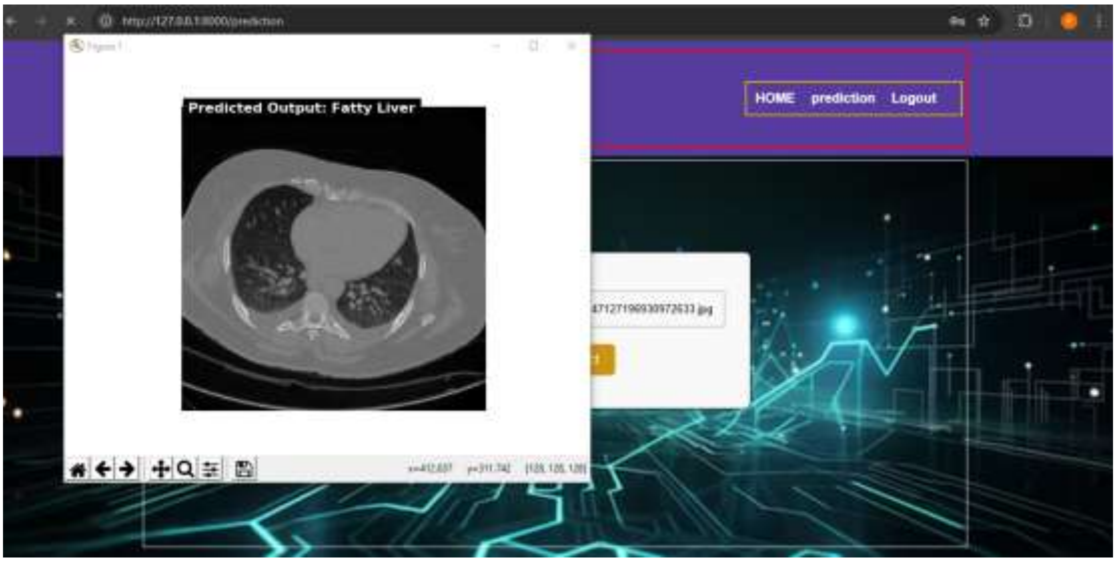

Fig.7: Prediction

5. CONCLUSION

The liver disease prediction system utilizing deep learning techniques has successfully demonstrated its ability to classify liver conditions, including Fatty Liver, Hepatocellular Carcinoma, and Liver Cirrhosis, based on medical image analysis. By leveraging a well-structured dataset and an optimized Convolutional Neural Network (CNN) model, the system achieves high accuracy in detecting and categorizing liver diseases. The integration of Principal Component Analysis (PCA) for dimensionality reduction and Simplified Social Spider Optimization (SSO) for hyperparameter tuning has significantly improved model performance, reducing computational complexity while maintaining robust diagnostic precision.

The proposed system enhances traditional diagnostic methods by providing an automated, efficient, and objective approach to liver disease classification. Unlike conventional medical diagnostics that rely on manual interpretation by radiologists, this AI-driven solution minimizes human error and accelerates the diagnostic process. The implementation of advanced image preprocessing techniques ensures that the model receives high-quality, noise-free input, leading to more reliable predictions.

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